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Hybrid frequency-domain and machine learning framework for image noise classification and adaptive restoration

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Abstract

Classification and restoration of envision noise are important problems in digital image processing that affect computer vision, medical imaging, and multimedia applications. This paper presents a sophisticated framework that addresses many noise types, such as Gaussian noise, impulse noise, motion blur, and speckle noise, by combining frequency-domain analysis, machine learning, and customized restoration algorithms. The method captures unique noise signatures by using the Discrete Cosine Transform (DCT), Discrete Fourier Transform (DFT) and the Fast Fourier Transform (FFT) to extract subtle frequency-domain properties. Several classifiers are investigated to achieve accurate noise type detection. A thorough assessment of the framework's flexibility and scalability is provided by this dataset, which includes a variety of distortions and noise levels.

Adaptive, noise-specific filtering algorithms that are in line with the recognized noise type are used by the system for noise restoration. A combination of bilateral and Gaussian filters is used to handle Gaussian noise, and sophisticated median and outlier-suppression

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techniques are used to recover impulse noise. Adaptive and wavelet-based filters reduce speckle noise, whereas Wiener filtering and deconvolution are used to fix motion blur.

Superior performance is demonstrated by extensive experimental data, which show notable gains in classification accuracy, structural similarity index measure (SSIM), and peak signal-to-noise ratio (PSNR). By establishing a comprehensive pipeline for reliable noise classification and restoration, this study shows how machine learning and frequency-domain analysis can be used to address practical issues in image quality improvement.

Subject Classification: *68U10, 68T07.*

Keywords: *Noise classification, Frequency domain analysis, Discrete domain analysis, Hybrid features, Image quality improvement, Noise restoration.*

1. Introduction

In image processing and computer vision, image noise categorization and restoration are essential operations that improve image quality for more accurate analysis and improved visual perception. In disciplines such as computer vision, remote sensing, and medical imaging, noise introduced during image acquisition, transmission, or storage can skew crucial features and make images less useful. Noise classification is the process of determining the kind of noise that is present in an image, such as motion blur, impulse noise, Gaussian noise, or speckle noise. While it enables the deployment of certain denoising techniques suited to the properties of each noise category, accurate categorization is crucial.

Conversely, denoising aims to restore images to their original quality by minimizing or getting rid of noise while preserving crucial characteristics like borders and textures. Spatial-domain filters like Gaussian and median filters as well as more complex approaches like deconvolution and non-local means are examples of advanced denoising techniques. The kind and intensity of the noise, as well as the intended trade-off between noise mitigation and detail preservation, all impact the method selection.

Effective restoration starts with noise labeling since it facilitates the application of particular denoising algorithms based on the type of noise. In this work, images are classified according to their noise patterns using frequency-domain analysis techniques as the Fast Fourier Transform (FFT), Discrete Cosine Transform (DCT), and Discrete Fourier Transform (DFT). These methods function by converting the image's spatial domain into the frequency domain, which makes noise patterns quicker to figure out. Targeted restoration techniques are used to enhance image quality after the type of noise has been detected. Gaussian Blur is a technique for reducing high-frequency noise in Gaussian noise while maintaining edges. Although it rapidly avoids outliers without surrendering fine features, median blur is used for impulsive noise. To address speckle noise, Fast Non-Local Means (FastNLMeans) averages similar patches through the image. Richardson-Lucy Deconvolution is an imaging method that gradually reverses the blurring process to reassemble motion-blurred images. Inpainting is used to restore areas that are missing or occluded in photos that include white overlay noise, and Gaussian Blur is added for seamless transitions.

Modern image processing systems offer notable improvements in image quality through the integration of targeted denoising techniques with noise classification. This enables for improved performance in tasks such as visual perception studies, medical diagnosis, and object recognition. This comprehensive approach emphasizes the significance the truth is understanding the properties of noise while applying appropriate restoration techniques in order to handle practical image processing issues.

2. Literature Survey

Deep convolutional neural networks [13] were proposed by Liu and Lam [1] to denoize images with poisson noise. For poisson noise denoising, block-matching and 3D filtering with variance stabilizing transformation (VST) were employed. For training and testing, images from the PASCAL Visual Object Classes database were utilized. The strength of noise was determined using the signal-to-noise ratio, peak signal-to-noise ratio, and mean squared error.

The Berkeley segmentation dataset was used for experiments by Jain and Seung [2]. A gaussian noise level was utilized to optimize the denoising process using the Bayes Least Squares-Gaussian Scale Mixture (BLS-GSM) approach. BLS-GSM, Fields of Experts (FoE), and convolutional network non-blind denoising results. Outstanding outcomes compared to the most advanced Markov random field (MRF) and wavelet techniques.

Using wavelet thresholding techniques, Kumar and Agarwal [3] experimented on several kinds of noise types, including poisson, gaussian, speckle, and salt-pepper. By specifying an appropriate threshold value, strategies like hard thresholding are frequently used to remove noisy coefficients. Metrics that quantify the enhancements in image quality, such as MSE, PSNR, RMSE, SNR, and SSIM, are used to assess the effectiveness of denoising techniques perform. This investigation provides insights regarding the manner wavelet-based denoising improves both statistical and perceived quality.

Momeny et al. [4] employed VGG-Net and NR-CNN techniques to classify picture noise. Various noise kinds, such as impulse and controlled noises, were worked on. In comparison to VGG-Net-Medium, VGG-Net-Slow, GoogleNet, and ResNet, experimental findings showed that the suggested CNN performs better in the categorization of noisy images. Training has been performed with the ILSVRC-2012 dataset.

For CNN image denoising, GAN was the most used technique, according to Ilesanmi and Ilesanmi [5]. Places2, BSD, the Waterloo Exploration Dataset, the COCO Dataset, and ImageNet Large Scale Visual Recognition Challenge Object Detection (ILSVRC-DET) make up the datasets that contain numerous images. The parameters for PSNR, SSIM, RMSE, FSIM, and SNR were employed as performance evaluation standards.

The noise estimation approach proposed by Kamble and Bhurchandi [6] has been employed to evaluate the quality of images. Experiments were conducted using the Computational Perception and Image Quality (CSIQ) and LIVE databases. A metric for evaluating the quality of images distorted by Gaussian noise includes the Differential Mean Opinion Score (DMOS). Noise has been calculated using the Discrete Wavelet Transform technique.

Roy et al. [7] employed CNN for image noise classification and denoising autoencoder (DAE) to recover original images from noisy shots. CNN, DAE-CNN, and DAE-DAE-CNN were used to categorize images that have been contaminated by zero, regular, and enormous sounds, respectively. Various noise levels from the MNIST handwritten numeral dataset were utilized.

Mixed-noise, which incorporates additive white Gaussian noise (AWGN) and impulse noise (IN), was a focus of an investigation by Islam et al. [8]. The process is recommended to use a convolutional neural network (CNN) model to lessen the mixed Gaussian-impulse noise present in photos. PSNR and SSIM have been employed as performance evaluation metrics in the Places2 and ImageNet Large Scale Visual Recognition Challenge (ILSVRC) 2015 object detection (DET) databases.

VGG-16 and Inception-v3 emerged by Sil, Dutta, and Chandra [9] to automatically recognize multi-type noise distribution. Gaussian, salt-peper, speckle, and other noise types were examples of multi-noise types. For image denoising, FFDNet employs the recently unveiled CNN architecture. The outcome assessment standards comprised PSNR and SNR.

An approach for immediate fashion high density impulse noise reduction from visuals was presented by Hosseini, Hessar, and Marvasti [10]. After applying an Efficient Weighted Average (EWA) filter to identify impulse noise, the image is stored. Closest-Pixel Map (CPM) and Distance Matrix (DM) were utilized to recover the image. Visual quality and PSNR were employed as performance metrics. Results from investigations perform better across both qualitative and quantitative metrics.

A unique approach based on statistical features with a neural network classifier was presented by Vasuki et al. [11] for distinguishing between numerous noise forms, including additive white Gaussian noise, salt and pepper noise, and speckle noise. SAR images from the DARPA Moving and Stationary Target Acquisition and Recognition (MSTAR) database as well as live photos are used. KNN and Neural Networks were utilized as classifiers for envision noise classification.

Saxena et al. [14] worked on multiple edge detection methods using Sobel, Prewitt, Roberts and canny operators. For evaluation, Mean squared error and peak signal to noise ration were used. Results were compared to detecting most efficient detecting function for increasing mammogram visual analysis.

Jain, Rajpal, and Soni [15] proposed a Least Square Support Vector Machine based framework for findings differenct sclerosis from MRI images. ROI methods and histogram equalization methods were used for segmentation, Gaussian filtering. And results were calculated using accuracy and Dice similarity metrics.

3. Methodology

The procedure starts with the acquisition of noisy images, which are utilized as the process's input. These images are subjected to noise classification, in which statistical techniques or machine learning models determine the kind of noise such as motion blur, speckle noise, or Gaussian distortion that is present. Upon the identification of the specific kinds of noise, the measured distortions can be reduced by applying the proper noise reduction algorithms. After noise reduction, the procedure moves on to picture restoration, where more improvements are made to bring back the original characteristics and caliber of the image. The denoised image is then produced, providing a clear, excellent outcome appropriate for additional use or examination.

Figure 1 shows workflow of a system.

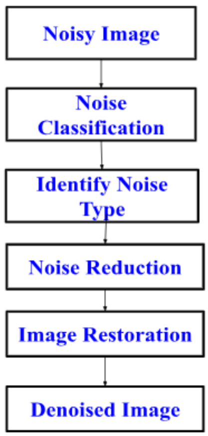


Figure 1
Workflow

3.1 *Noise classification*

A noisy image is processed using the methodology in order to classify and determine several types of noise, including motion blur, impulse, white overlay, speckle, and Gaussian noise. Fast Fourier Transform, Discrete Cosine Transform, and Discrete Fourier Transform are among the methods used to extract features in order to find patterns linked to each type of noise. To properly classify the noise, the gained patterns are further fed into classifiers such as Random Forest, Naïve Bayes, and Support Vector Machine. The utilization of excellent noise reduction and image restoration techniques is made possible by this rigorous approach, which provides accurate noise type identification.

3.1.1 Feature Extraction Techniques:

(a) Fast Fourier Transform (FFT): FFT renders the frequency spectrum visible by transforming a picture into the frequency domain, which makes it possible to spot recurring patterns and periodic noise features. It is especially helpful for identifying patterns of global noise.

$$F(u,v) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} I(p,q) * e^{-j2\pi(up/M + vq/N)} \quad (10)$$

where, I (p, q) is intensity of the pixels at coordinate at (p, q),

F (u, v) is the representation of frequency at (u, v),

M and N are the dimensions of the image,

j = √-1 is the hypothetical unit.

Inverse FFT

Utilize the Inverse FFT to transform the filtered frequency spectrum back into the spatial domain.

$$I'(p,q) = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} F_{filtered}(p,q) * e^{j2\pi(up/M + vq/N)} \quad (2)$$

where, I'(p, q) represents Restoration image. And $F_{filtered}$ (p, q) denotes frequency spectrum.

(b) Discrete Cosine Transform (DCT): A finite series of data points is quantified by DCT as a sum of cosine functions that wobble at various frequencies. Its strong energy compaction qualities and widespread use in picture compression make it useful for identifying minor noise patterns and differentiating between noise kinds.

$$C(u,v) = \boldsymbol{\alpha}(u) * \boldsymbol{\alpha}(v) \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} I(p,q) * \cos[\frac{\pi}{M} * u * \left(x + \frac{1}{2}\right)] * \cos[\frac{\pi}{N} * v * \left(y + \frac{1}{2}\right)] \quad (3)$$

where, C(u,v) denotes DCT frequency component in transformed image.

I(p,q) is intensity of the pixels at coordinate at (p,q).

M and N represents dimension of the image.

(u) and $\boldsymbol{\alpha}$(v) Normalization factors.

Inverse DCT

$$I''(p,q) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \boldsymbol{\alpha}(u) * \boldsymbol{\alpha}(v) * C(u,v) * \cos[\frac{\pi}{M} * u * \left(p + \frac{1}{2}\right)] * \cos[\frac{\pi}{N} * v * \left(q + \frac{1}{2}\right)] \quad (4)$$

where, C(u,v) denotes DCT coefficient at (u,v)

I''(p,q) is the reconstructed image.

M and N represents dimension of the image.

(u) and $\boldsymbol{\alpha}$(v) Normalization factors.

(c) Discrete Fourier Transform (DFT): By assessing the frequency content of finite sequences, DFT can provide clues about the periodic structures present in a picture. DFT is used for a wider variety of tasks, such as analyzing intricate noise patterns. Convert image intensity variations into sinusoidal frequency component.

$$F(u,v) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} I(p,q) * e^{-j2\pi(up/M + vq/N)} \tag{5}$$

where, I(p,q) is intensity of the pixels at coordinate at (p,q),

F(u,v) is the representation of frequency at (u,v),

M and N are the dimensions of the image,

j = √-1 is the hypothetical unit.

Inverse DFT:

$$I'''(p,q) = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} F_{filtered}(p,q) * e^{j2\pi(up/M + vq/N)} \tag{6}$$

where, I'''(p,q) represents DFT Restoration image. And $F_{filtered}$ (p,q) denotes frequency spectrum.

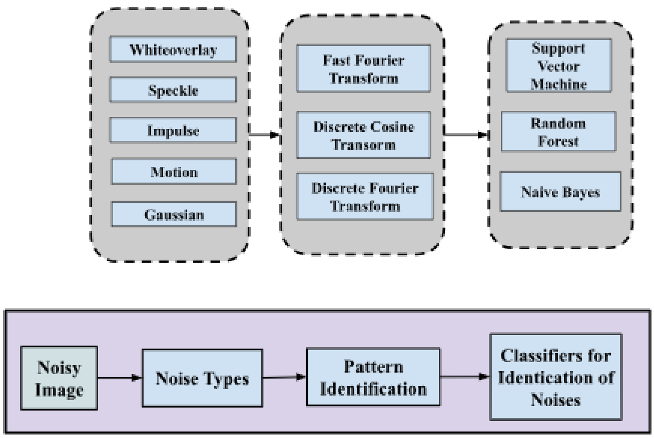


Figure 2
Noise Classification Methodology

Figure 2 describes the methodology that used for Various Image Noise Classification.

3.1.2 Classifiers:

a) Support Vector Machine: SVM is a supervised learning technique that improves the margin between classes in determining the best hyperplane to divide them. It may be applied to complicated decision boundaries with various kernels and performs well in high-dimensional spaces [15].

b) Random Forest: An ensemble learning technique called Random Forest constructs many decision trees and aggregates their results to classify data. Reducing overfitting and increasing accuracy by averaging predictions from several trees trained on random samples of data.

c) Naïve Bayes: Naive Bayes is a probabilistic classifier that assumes feature independence and is based on Bayes' theorem. It works well with small datasets and is computationally economical, particularly for text classification and picture noise.

3.2 *Noise Reduction:*

Various approaches to noise reduction are used according to the type of noise that has been defined. Successful approaches for reducing various kinds of noise include Richardson-Lucy deconvolution, Gaussian Blur, Median Blur, and Fast NL Means. Gaussian Blur is applied in conjunction with inpainting for complex instances, such as white overlay. The finished process yields a clear, denoised image that is prepared for other uses. This methodical process guarantees focused and effective noise reduction.

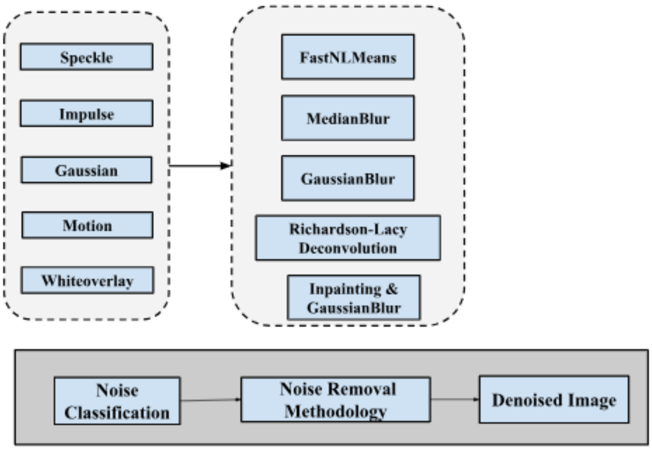


Figure 3
Noise Denoising Methodology

Figure 3 shows the working flow of Image Noise Reduction for various Noises using Multiple filters.

4. Performance Evaluation Criteria

Three basic performance evaluation criteria regulate the evaluation of real accuracy across various frequency function patterns and restoration parameters, each of which is a crucial indicator for analytical precision and comparative analysis.

(A) *Accuracy*

The primary measure in classification jobs is accuracy, which is the percentage of properly identified examples out of all the instances assessed.

Accuracy in the context of image noise classification measures how well a model recognizes the kind of noise that is present in imagery.

$$\text{Accuracy} = \frac{NumberofpreciselyPredictions}{TotalNumberofPredictions} * 100\ \% \tag{7}$$

A more successful categorization model is indicated by a greater accuracy.

(B) *Peak Signal-to-Noise Ratio (PSNR)*

A popular measurement for evaluating the quality of reconstructed images adhering to compression or denoising is PSNR [14]. It assesses the ratio between the highest signal strength and the power of corrupting noise by comparing the original and processed images.

$$\text{PSNR} = 20\ \log10\ (\text{MAX}_i\ /\ \sqrt{MSE}) \tag{8}$$

where, MAX_i is the picture's maximum pixel value (for example, 255 for an 8-bit image).

The formula for calculating MSE (Mean Squared Error) is:

$$\text{MSE} = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [\ I(i,j) - K(i,j)\ ]^2 \tag{9}$$

I indicate the original image, K for the processed (denoised), and m and n for the image's dimensions.

Better image quality is demonstrated by greater PSNR values, which are measured in decibels (dB). PSNR, however, might not necessarily match how well a picture appears to the human eye.

(C) *Structural Similarity Index Measure (SSIM)*

A SSIM rating of 1 denotes complete structural similarity between the pictures; values range from -1 to 1. SSIM frequently has a stronger correlation with human eye evaluations of picture quality than PSNR [14].

$$\text{SSIM}(x,y)=(2\boldsymbol{\mu}_x\boldsymbol{\mu}_y+C_1)(2\sigma_{xy}+C_2)/(\boldsymbol{\mu}_x^2+\boldsymbol{\mu}_x^2+C_1)(\boldsymbol{\mu}_x^2+\boldsymbol{\mu}_x^2+C_2) \tag{10}$$

Mean intensities of pictures x and y are denoted by μ_x and μ_y.

$\boldsymbol{\mu}_x^2$ and $\boldsymbol{\mu}_y^2$: Images x and y that differ from one another.

The covariance of pictures x and y is represented by σ_{xy}.

Stabilization constants C_1 and C_2 are used to avoid division by zero.

5. Result

The findings indicate that the classifier and the pattern identification technique have an influence on the classification accuracy. In most situations, FFT and DFT work well, but RF has the best accuracy, particularly where it comes to motion noise (100%). All approaches reliably classify white-overlay noise with high accuracy. DCT has trouble, particularly with SVM, which does not do well with motion and speckle noise. All things considered, RF is the best classifier, especially when combined with FFT or DFT. Table 1 presents the accuracy results of the noise classification process.

Table 1
Accuracy of a Noise Classification

Pattern Identification Methodology	Classifier	Noises Types				
		Gaussian	Speckle	White-overlay	Impulse	Motion
FFT	RF	63.75	87.26	91.84	58.29	100.00
FFT	SVM	54.30	83.39	90.55	62.21	94.81
FFT	Naive Bayes	46.52	85.59	86.67	59.14	73.82
DFT	RF	63.93	87.26	91.84	57.75	100.00
DFT	SVM	60.36	75.58	79.08	47.77	96.43
DFT	Naive Bayes	50.71	86.73	67.73	65.06	100.00
DCT	RF	30.89	58.94	97.87	31.55	87.50
DCT	SVM	54.29	9.56	94.50	19.25	1.82
DCT	Naive Bayes	7.50	59.82	91.49	36.72	44.64

Using a variety of feature extraction and categorization techniques, the table contrasts the accuracy of five different forms of noise. The best accuracy for Speckle, White Overlay, and Motion noise was obtained by FFT+RF and DFT+RF, which even reached 100% for Motion. For White Overlay, DCT+SVM worked well (94.50%), but it did poorly for other kinds of noise. FFT+RF and DFT+RF showed moderate accuracy for Gaussian and Impulse noise.

Image Denoising Results:

(A) *White Overlay Noise Reduction using Integration of Inpainting and Gaussian Blur.*

Noisy Image Denoised Image

Figure 4
White-overlay Noise Image Restoration

The restored image after removing white-overlay noise is shown in Figure 4.

Table 2

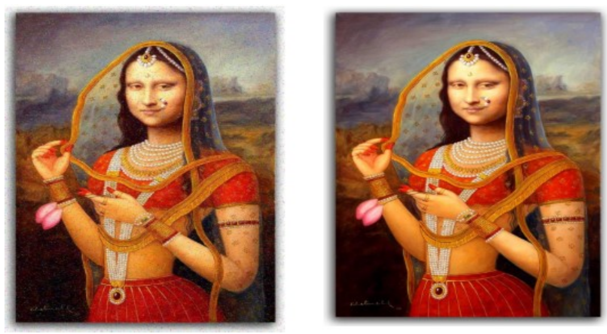
Performance of Denoised Image

PSNR Values		SSIM Values	
Noisy	**Restored**	**Noisy**	**Restored**
10.43	15.60	0.6798	0.7524

The performance results of the denoised image are given in Table 2. The integration of inpainting and Gaussian blur enhances image quality, increasing PSNR from 10.43 to 15.60 and SSIM from 0.6798 to 0.7524, indicating effective noise reduction and structural improvement.

(B) *Impulse Noise Reduction using Median Blur Filter*

Figure 5 presents the result of impulse noise image restoration.



Noisy Image Denoised Image

Figure 5

Impulse Noise Image Restoration

The performance of the denoised images is presented in Table 3.

Table 3

Performance of Denoised Image

PSNR Values		SSIM Values	
Noisy	**Restored**	**Noisy**	**Restored**
21.83	28.05	0.4693	0.8294

The Median Blur filter is a nonlinear noise reduction technique that effectively removes impulse noise while preserving edges. [12, 14] Applying this method increases PSNR from 21.83 to 28.05 and significantly improves SSIM from 0.4693 to 0.8294, indicating better image quality and structural preservation.

(C) *Motion Noise Reduction using Richardson -Lucy Deconvolutional Method*

The motion noise removal result can be seen in Figure 6.

Noisy Image Denoised Image

Figure 6

Motion Noise Image Restoration

Table 4

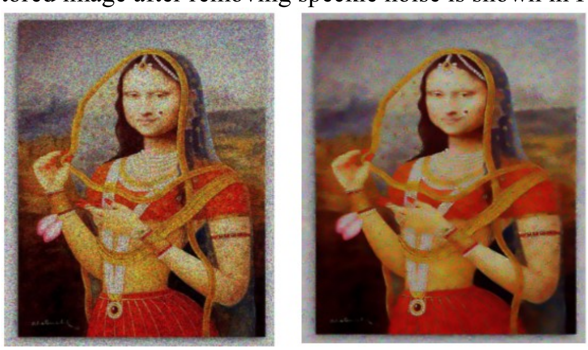
Performance of Denoised Image

PSNR Values		SSIM Values	
Noisy	**Restored**	**Noisy**	**Restored**
18.99	13.32	0.6961	0.5589

The denoised image performance results are given in Table 4. The Richardson-Lucy deconvolution method applied for motion noise reduction results in a decrease in PSNR from 18.99 to 13.32 and SSIM from 0.6961 to 0.5589, suggesting potential over-processing or artifacts introduced during restoration

(D) *Speckle Noise Reduction using Fast-NL Means Method*

The restored image after removing speckle noise is shown in Figure 7.



Noisy Image Denoised Image

Figure 7

Speckle Noise Image Restoration

Table 5

Performance of Denoised Image

PSNR Values		SSIM Values	
Noisy	**Restored**	**Noisy**	**Restored**
11.93	12.45	0.4710	0.5078

The denoised image performance for speckle noise can be seen in Table 5. The Fast-NL Means method slightly enhances image quality by increasing PSNR from 11.93 to 12.45 and SSIM from 0.4710 to 0.5078, indicating modest noise reduction.

(E) *Gaussian Noise Reduction using Gaussian Blur Method*

Figure 8 shows the restoration image after removal of Gaussian noise.

Noisy Image Denoised Image

Figure 8

Gaussian Noise Image Restoration

Table 6

Performance of Denoised Image

PSNR Values		SSIM Values	
Noisy	**Restored**	**Noisy**	**Restored**
18.28	24.04	0.2751	0.6598

Table 6 shows the performance of the denoised images for Gaussian Noise. The Gaussian Blur method effectively reduces Gaussian noise, increasing PSNR from 18.28 to 24.04 and improving SSIM from 0.2751 to 0.6598.

PSNR and SSIM are successfully improved by the restoration procedure for a large number of noise types, with notable improvements shown for Impulse and Gaussian noise in particular. However, the quality of the images decreases after motion noise restoration, suggesting possible over-smoothing or artefacts. The lack of improvement in speckle noise suggests that the current approach has trouble eliminating it.

6. Conclusion

The results indicate that the most dependable approaches for classifying noise are FFT and DFT, particularly when combined with the RF classifier. The performance of DCT is poorer, and it is less effective in differentiating between different kinds of noise. While speckle and impulse noise exhibit varying degrees of accuracy depending on the technique, motion noise is the most straightforward to categorise. These findings suggest that for robust noise categorisation, RF with FFT or DFT is appropriate. For both Gaussian and Impulse noise, the restoration method performs admirably. Speckle noise could necessitate specific filtering techniques, whereas motion noise requires more refining to manage without sacrificing quality.

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